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Procedia Engineering 53 (2013) 411 – 419
Procedia Engineering
www.elsevier.com/locate/procedia

Adaptive Boosting with SVM Classifier for Moving Vehicle Classification

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Abstract

Profoundly hearing impaired community (PHIC) cannot moderate wisely an acoustic noise emanated from moving vehicle in outdoor. They are not able to distinguish either type or distance of moving vehicle approaching from behind. Therefore, the PHIC encounter risky situation while they are in outdoor. In this paper, a simple system has been proposed to identify the type and distance of a moving vehicle using adaptive boosting (AdaBoost) ensemble method. One-third-octave filter band approach has been used for extracting the significant features from the noise emanated by the moving vehicle. The extracted features were associated with the type and distance of the moving vehicle. A support vector machines (SVM) has been used as a weak classifer during the AdaBoost classification. The AdaBoost classification system outperforms the single classifier system in terms of classification accuracy.

Selection and peer-review under responsibility of the Research Management & Innovation Centre, Universiti Malaysia Perlis

Keywords: *Moving Vehicle; Adaptive Boosting; Support Vector Machine; One-Third-Octave*

1. Introduction

Acoustic noise signatures emanated from a moving vehicle along the roadside are mainly influenced by the engine vibration and the friction between the tires and the road. The vehicles of similar type and working in a similar condition posses almost similar noise signatures [1]. This pattern of noise signature is used for classifying the type of vehicle and their distance from the subject.

Recently, a number of studies have been made for recognizing noise or sound signature of a moving vehicle based on its sound signature. Henryk Maciejewski et. al. [2] developed a neural classifier to classify the type of moving vehicles based on the noise produced by the vehicle engine and also by the carriage devices. Wavelet method has been used for feature extraction. Similar feature extraction methods also have been made by Amir Averbuch [3, 4]. Huadong Wu et. al. [1] proposed a frequency vector principle to recognize the moving vehicles based on its sound signature. Eom [5], using time-varying autoregressive models expanded by a low-order discrete cosine transform classified the type of moving vehicles. Bayesian subspace methods based on the short term Fourier transforms has been proposed by Munich [6] to recognize the type of the moving vehicles. A simple approach based on nonlinear Hebbian learning has been implemented by Bing Lu et. al. [7] to classify the type of moving vehicles. Hanguang et. al.[8] proposed short-time Fourier transform and detected the type of moving vehicles using principal component analysis.

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1877-7058
Selection and peer-review under responsibility of the Research Management & Innovation Centre, Universiti Malaysia Perlis
doi:10.1016/j.proeng.2013.02.054

Based on literature, it has been observed that most of the authors have dealt only with the recognition of the vehicle types. The distance between the hearing impaired and the approaching vehicle from their behind is a very important criterion, and this criterion has not been considered by early researchers. Hence, in this research work [9, 10], a simple scheme has been proposed to identify the type as well as the distance of the moving vehicles based on the noise emanated by them. The maximum distance from the subject to the moving vehicle is considered as 100 meters. When the moving vehicle is approaching the subject from a distance of 100 meters, the noise emanated from the vehicle is continuously recorded till it crosses the observer. The one-third-octave band frequency spectrum of the noise was extracted and associated to the type and distance of the moving vehicle. The developed feature set was then used to model an AdaBoost ensemble method with support vector machine (SVM) as a weak classifier.

2. Research Methodology

The noise emanated from a moving vehicle is recorded using a digital voice recorder (Sony, ICD-SX700). The recording was performed along the section of the road from Ulu Pauh to Padang Besar. The average speed of the vehicles along this road is between 50 – 70 km/h. Two different locations along the section of the road were considered and marked as A and B as shown in Fig. 1. The distance between the locations A and B is 100 meters. The digital sound recorder was placed at the point B. The noise emanated from a vehicle was continuously recorded as it was traversing towards the point B from the point A. The time taken by the vehicle to traverse the distance AB was also observed.

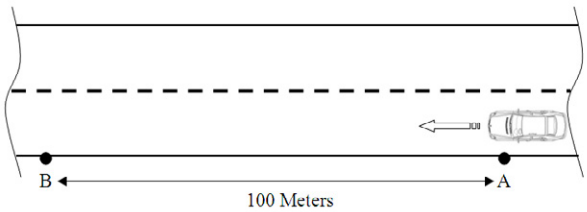

Fig. 1. Data collection

The noise emanated by the vehicle is recorded at a sampling frequency of 44100 Hz and has been down sampled to 22050 Hz for analysis. Then, the signal is divided into five equal zones as shown in Fig. 2. The signals obtained from the first four zones were considered in the analysis. The last zone is not considered as it is very near to the target. For each zone signal, the feature coefficients are obtained using frequency-domain analysis. These coefficient values are then associated to the respective zone number as well as to the type of vehicle and used to develop an ensemble classifier based on adaptive boosting (AdaBoost).

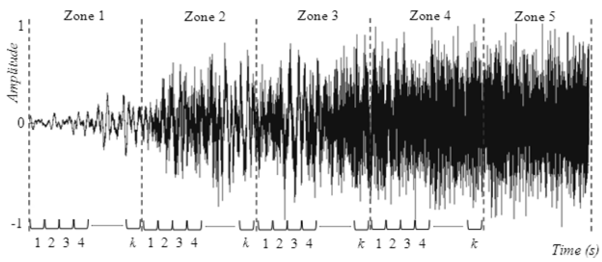

Fig. 2. Zone separation for typical signal

3. Feature Extraction Research Methodology

Frequency analysis is a process used to transform a time-domain signal into a frequency domain. Number of methods can be used to analyse the frequency-domain. In this paper, one-third-octave frequency spectrum analysis has been performed as it is one of the most popular audio analyses. The recorded noise signal emanated is divided into frames such that each frame has 1024 samples. Frame overlapping has not been considered in this analysis. For each frame, the frequency response has been extracted using a simple bandpass Butterworth filter [11] as shown in Fig. 3.

The center frequencies of the different bands $f_c(k)$ are defined relative to a bandpass filter centered at $f_c(0)$ = 1000 Hz. The bandpass centre frequencies are computed using Equation 1. Equation 2 and 3 are used to compute the lower and upper band frequencies. The k-th bandwidth (Bw) and the sound pressure level (L) with reference $p_0=20\mu Pa$ are computed using Equation 4 and 5 respectively. The discriminations in the energy levels for the various sub-band frequencies are extracted and used as training features to classify the type and distance of the moving vehicle. The centre frequencies for the 18 one-third-octave bands along with the lower and upper cut-off frequencies are shown in Table 1.

$$f_c(k) = 2^{k/3} \times 1000 \tag{1}$$

$$f_l(k) = \frac{f_c(k)}{2^{1/6}} \tag{2}$$

$$f_u(k) = f_c(k) \times 2^{1/6} \tag{3}$$

$$B_w = \frac{f_c(k)}{f_u(k) - f_l(k)} \tag{4}$$

$$L(k) = 10\log_{10}\left(\frac{p(k)^2}{p_o^2}\right) \tag{5}$$

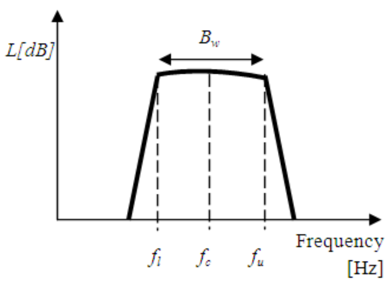

Fig. 3. One-third-octave filter bandsTable 1 One Third Octave Band Frequency

Table 1: One-Third-Octave Band Frequency

Bands	Center Frequency (Hz)	Upper Cut-off Frequency (Hz)	Lower Cut-off Frequency (Hz)
1	100	112	90
2	126	140	112
3	160	180	140
4	200	224	180
5	250	280	224
6	315	355	280
7	400	450	355
8	500	560	450
9	630	710	560
10	800	900	710
11	1000	1120	900
12	1250	1400	1120
13	1600	1800	1400
14	2000	2240	1800
15	2500	2800	2240
16	3150	3550	2800
17	4000	4500	3550
18	5000	5600	4500

4. Boosting

Boosting is a method in machine learning to turn the weak classifier into a stronger classifier [12]. The main idea of boosting is to build many complement classifiers in order to find a highly accurate classifier on the training set by ensemble the weak hypothesis. The most popular boosting algorithm is adaptive boosting (AdaBoost) [13, 14].

4.1. Boosting

AdaBoost is a direct extension [13] from boosting algorithm and it is known as AdaBoost.M1. This ensemble method has been applied in many applications such as speech recognition [15], Alzheimer's detection [16], moving vehicle classification based on images [17-19] and etc. Based on literature, this ensemble method has not been used for moving vehicle noise classification. Most of the authors have developed only strong individual learner for the overall classification. AdaBoost.M1 has the capability to generate the hypothesis from the possible labels. During training, the prediction error for the weak hypothesis should be less than 0.5 [13]. The objective of distribution is to select the 'hard' training data and sample back for the next iteration. AdaBoost.M1 generates a set of hypothesis and ensemble through weighted majority voting of the classes from the prediction by individual hypothesis. Support vector machine (SVM) has been used as the individual hypothesis. The pseudocode of AdaBoost.M1 is shown in Fig. 4.

Algorithm 1: The AdaBoost.M1

Input: Sequence of N examples, $S = \{(x_1, y_1), \ldots (x_N, y_N)\}$, $x_i \in X$, with labels
$y_i \in Y = \{\omega_1, \ldots, \omega_C\}$, where ω_i is number of classes.
Weak classifier algorithm (*K*-Nearest Neighbor).
Number of Learning Rounds, T.

Initialize: Distribution: $D_i^t = \frac{1}{N}, i = 1, \ldots, N$
Neighbor(s): $K = m., \ 1 \le m \le N$

Do for: $t = 1, 2, \ldots, T$

1. Select the subset training data S_t, drawn from the distribution D^t.
2. Train the base classifier with S_t and receives the hypothesis h_t.
   $h_t : X \rightarrow Y$
3. Calculate the error of h_t.
   $h_t : \varepsilon_t = \sum_i^N D_i^t \times e_i^t$, where $e_i^t \begin{cases} (h_t(x_i) \neq y_i) = 1 \\ (h_t(x_i) = y_i) = 0 \end{cases}$
   If $\varepsilon_t > 0.5$, then set $T = t\text{-}1$ and abort the loop
4. Set weight, $\beta_t = \frac{\varepsilon_t}{1 - \varepsilon_t}$
5. Update distribution
   $D^t : D_i^{t+1} = \frac{D_i^t}{Z_t} \times \varphi_t$, where $\varphi_t \begin{cases} (h_t(x_i) = y_i) = \beta_t \\ (h_t(x_i) \neq y_i) = 1 \end{cases}$
   Where $Z_t = \sum_i^N D_i^t$ is normalization constant for D_i^{t+1} become a proper distribution.

Output: Given an unlabelled instance $\boldsymbol{x}$. Choose the class that have highest total vote as final classification.

$$h_f(x) = \arg\max_{y \in Y} \sum_{t=1}^{T} \log \frac{1}{\beta_t} \times v, \text{ where } v \begin{cases} (h_t(x) = \omega_j) = 1 \\ (h_t(x) \neq \omega_j) = 0 \end{cases}$$

Fig. 4. Pseudocode of AdaBoost.M1 algorithm with SVM weak learner [13]

4.2. Support Vector Machines (SVM) Classifier

Support vector machines (SVM) are used to develop the individual hypothesis. SVM is a popular algorithm used in learning machine. It can be used for classification, regression and other learning task [20]. The SVM is capable of learning high dimensional space with a few of training data [21]. The basic concept of SVM is to search an optimal separating in hyperplane, whereas it can separate two classes. The separating boundary is in general form with kernel trick is shown in Equation 6.

$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b \right) \tag{6}$$

where, N is number of training data sample, $0 \le \alpha_i \le C, i = 1, 2, \ldots, N$ are non negative parameter learned from the data. C is a penalization misclassification cost parameter used in training data sample. For larger C the training performance is better and poor generalization otherwise. x_i are the support vectors, b is a bias, y_i are the labels($y_i \in \{+1, -1\}$) and $K(x_i,x)$ is the kernel function. A radial basis function (RBF) kernel as shown in Equation 7 has been chosen, since it able to classify with high accuracy [21, 22]. From Equation 7, the adjustable parameter sigma (σ) is a major role for the RBF kernel to perform well. If the sigma is overestimated, the kernel exponential will behave almost linearly and if underestimated the regularization is lacked and decision boundary is sensitive to noise in training data [21].

$$K(x_i, x) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2} \right) \tag{7}$$

SVM was originally designed for binary classification [23, 24]. Generally, SVM has two approaches for multi-class problem namely, one-versus-one (OVO) and one-versus-rest (OVR) approach. For *m*-class, OVO generates *m(m-1)/2* classifiers and OVR generates *m* classifiers. Regarding to [23], OVO approach is more suitable for practical use and performed better than OVR even though the number of classifiers used are larger when compared to OVR. In this research work, there is a multi-class problem involves. Hence, OVO approach has been chosen and implemented.

4.3. Result and Discussion

Four different types of vehicles namely car, bike, truck and lorry are considered in this research. Table 2 depicts the number of vehicles observed and used in the analysis. The recorded noise signals were separated into frames such that each frame has 1024 samples. From each frame, 18 one-third-octave band frequency features were extracted [9]. The number of frames for each zone varies as it depends on the speed of the moving vehicle traversing from point A to point B. Features for four and six consecutive frames were average and associated to the vehicle type and zone respectively. The method of averaging from consecutive frames is depicted in Fig. 5. This process was repeated for the entire 140 recorded signal and a data set containing of 15160 samples for vehicle type and 14040 samples for vehicle zone were formulated.

Table 2 Type of vehicle

Type of Vehicle	**Sample**
Car	35
Bike	35
Lorry	35
Truck	35
Total	140

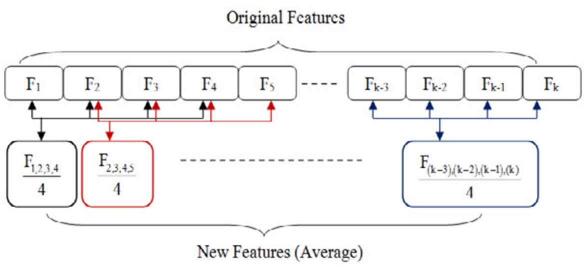

Fig.5. Features from four consecutive frame for averaging

The main dataset was randomized and normalized between -0.9 to +0.9. 70% of the samples were chosen for training and the remaining used for testing. To evaluate the SVM parameters, five runs were made. For each run, the main dataset was randomized and 5 best parameters were chosen based on the best cross validation accuracy. Then, from 25 possibility parameters (5 runs multiplied with 5 best); the 3 best parameters were chosen arbitrarily for comparison using AdaBoost.M1 algorithm. Table 3 shows the single classifier classification accuracy and SVM parameters used in AdaBoost.M1 for both vehicle type and zone classifiers.

Table 2 SVM Parameters and single classifier classification accuracy.

Parameters	Vehicle Type			Vehicle Zone		
	Accuracy (%)	*C*	σ	Accuracy (%)	*C*	σ
Best 1	86.86	16	8	86.14	16	16
Best 2	86.47	8	8	85.67	8	16
Best 3	86.12	4	16	84.10	4	16

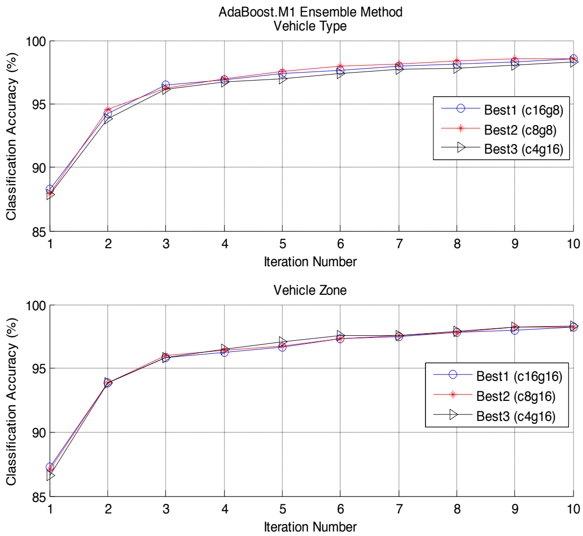

Fig. 6. AdaBoost.M1 Ensemble Method for Vehicle Type and Zone

For instance, 10 iterations were chosen for comparison with AdaBoost.M1 and single classifier. Fig. 6 shows the performance of AdaBoost.M1 for vehicle type and zone classifiers. It is shown that in Fig. 6, even though the number of iteration is small, AdaBoost.M1 can classify with better classification accuracy compared to single classifier.

The difference classification accuracy between single classifier with AdaBoost.M1 for vehicle type is shown in Fig. 7. This difference based on three best SVM parameters. From Fig. 7, the iteration begins from 1 to 5 the difference is gradually increased and then it begins to retain slightly. It is shown that in Fig. 7, even though the lower parameters (Best 3) it can produce better performance when using AdaBoost.M1. Meanwhile, Fig. 8 shows the difference classification accuracy between single classifier with AdaBoost.M1 for vehicle zone. The difference for vehicle zone gradually increase to begin from iteration 1 to 5 and then it slightly retains from 6 to 10. AdaBoost.M1 gives a better performance when the parameters are lower (Best 3). It is shown that for using the AdaBoost.M1 ensemble method, the weak classifier can be used since the AdaBoost.M1 can boost the 'hard' sample and produce better classification accuracy.

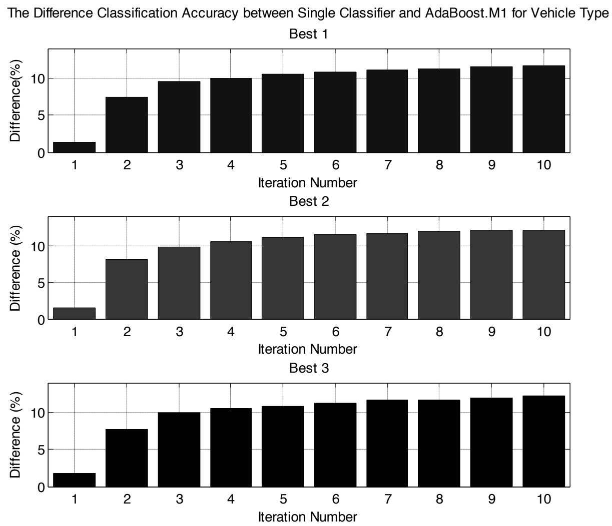

Fig. 7. The Difference Classification Accuracy between Single Classifier and AdaBoost.M1 for Vehicle Type

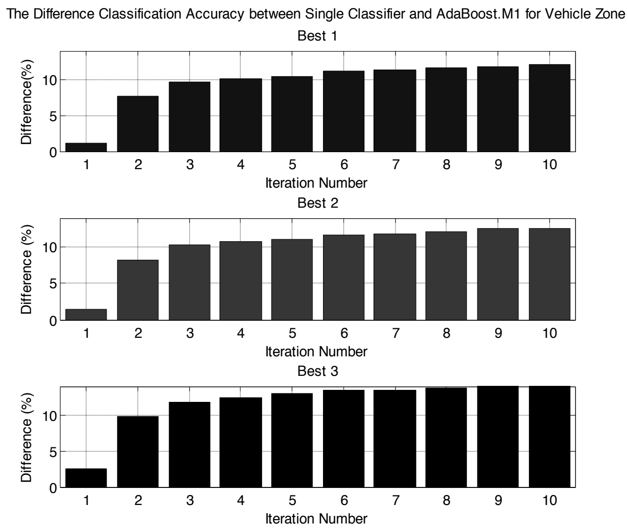

Fig. 8. The Difference Classification Accuracy between Single Classifier and AdaBoost.M1 for Vehicle Zone

5. Conclusion

Boosting is an ensemble method used for combining a simple classifier (weak classifier) to achieve the stronger classifier. The result shows that when the numbers of weak classifiers are increased the classification accuracy is also increases. The proposed method also gives a promising result for both vehicle type and zone classification. In the future work a theoretical analysis will be made for other weak classifiers using AdaBoost.M1.

Acknowledgements

The authors would like to acknowledge the support and encouragement by the Vice Chancellor of Universiti Malaysia Perlis, Brigadier Jeneral Dato' Prof. Dr. Kamarudin Hussin. This work is financially assisted by the Fundamental Research Grant Scheme (FRGS) (9003-00186): by the Ministry of Higher Education, Malaysia.

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